IQ in the Ramsey Model:
A Naïve Calibration

Garett Jones
Southern Illinois University Edwardsville

July 2005
Preliminary Version: Comments Welcome

I show that in a conventional Ramsey model, between one-fourth and one-half of income differences across countries can be explained by a single factor: The steady-state effect of large, persistent differences in national average IQ on worker productivity. These differences in cognitive ability--which are well-supported in the psychology literature--are likely to be malleable through better nutrition, better education, and better health care in the world's poorest countries. A simple calibration exercise in the spirit of Bils and Klenow (2000) and Castro (2005) is conducted. A move from the bottom decile of the global IQ distribution to the top decile will cause steady-state living standards to rise by between 75 and 350 percent. I provide evidence that little of the IQ-productivity relationship is likely to be due to reverse causality.

Contact Information: Garett Jones, Assistant Professor, Department of Economics and Finance, Southern Illinois University, Edwardsville, IL 62026. e-mail: garjone@siue.edu. http://www.siue.edu/~garjone

The author would like to thank economists Michael Davis and Petia Stoytcheva and psychologist W. Joel Schneider for helpful comments, and the Graduate School of Southern Illinois University Edwardsville for financial support. The usual disclaimer applies.

In this paper, I contend that between one-fourth and one-half of income differences across countries can be explained by a single factor: The effect of large, persistent differences in average national IQ on labor productivity. These differences in cognitive ability--which are well-supported in the psychology literature--are likely to be malleable through better nutrition, better education, and better health care in the world's poorest countries.

I arrive at this result through a short chain of reasoning: labor econometricians have shown that higher IQ causes higher wages (*inter alia*, Bowles, Gintis, and Osborne (2001), Cawley, Conneely, Heckman, and Vytlacil (1997), Zax and Rees (2002), Neal and Johnson (1996), and developing country estimates cited in Behrman et al., (2004)). In competitive markets, the reason for this higher wage is because higher IQ raises labor productivity. Finally, in a conventional Ramsey growth model, anything that raises labor productivity raises the steady-state capital-labor ratio, thus leading to a multiplier effect of IQ on labor productivity.

Formalizing this chain of thought within a quantitative general equilibrium setting, I use microeconometric estimates of IQ's impact on the marginal product of labor along with macroeconomic estimates of the elasticity of output with respect to capital to calibrate a simple Ramsey model of a nation's economy. This methodology takes into account the possibility of reverse causality, and in this respect is similar to Bils and Klenow (2000), who focused on the possibility of reverse causality in the cross-country education-growth relationship. My use of calibration in a cross-country setting is similar to (though simpler than) the innovative work of Castro (2005).

The theoretical model calibrated here helps explain why previous researchers (Lynn and Vanhanen (2002), Weede and Kampf (2002), Weede (2004), Jones and Schneider (2004)) have found strong statistical relationships between national average IQ and economic performance. For reference, I note that the simple correlation between log year 2000 output per worker and national average IQ (as measured by the Penn World Tables and Lynn and Vanhanen (2002), respectively) is 0.82 (Figure 1).

Multivariate tests have repeatedly demonstrated that this relationship between national average IQ and economic performance is robust (though see Volken (2003) and Nechbya (2004) for contrary views). For example, Jones and Schneider found that in 1330 Solow-style growth regressions that included only robust control variables, national average IQ was statistically significant in 99.8% of these regressions, and positive in 100% of these regressions; further, they found that IQ easily passed the Bayesian model averaging robustness test proposed by Sala-i-Martin, Doppelhofer, and Miller (2004).

IQ's correlation with cross-country differences in productivity and productivity growth demands a theoretical explanation: This calibration exercise is the beginning of such an explanation. The results presented here imply that depending on the capital elasticity of output parameter, a move from the bottom decile of the global IQ distribution to the top decile will cause a rise in steady-state living standards of between 75 and 350 percent. I close by discussing the opportunities for macroeconomists to explore policy interventions that can best close this large, persistent IQ gap.

The Relative Reliability of IQ

The crucial question in this line of inquiry is whether cross-country IQ measures are generally reliable. A large line of research in the psychology literature, going back for a hundred years and summarized in Lynn and Vanhanen (2002) demonstrates that when using best-practice psychometric methods, they generally are. After discussing IQ tests in general, I will then discuss cross-country and non-verbal IQ tests.

Tests of general cognitive ability--which I will refer to as IQ (Intelligence Quotient) tests--were originally developed for the Paris school system by Alfred Binet in 1908. Binet's tests were quickly found to be useful in identifying mentally retarded children (Jensen (1998), 15). IQ tests have had this practical orientation ever since: They are used by schools to place students, and they are widely used by the U.S. military to allocate human resources efficiently (Jensen (1998), 282ff.).

In addition, IQ tests are heavily used by firms to hire and promote (Cascio (2003), 250-251), and so it appears that such tests are a valuable source of information for firms about the quality of job applicants. In a meta-analysis reported in Cascio's (2003, 252) widely-used human resources text, such "general mental ability tests" are tied for third out of 19 predictors of job performance, ranking behind actual work samples and tied with structured employment interviews for statistical validity.

The validity of IQ tests in work settings is unambiguous. These scores correlate 0.3 to 0.5 with assessments of worker performance by managers—and are higher when job performance can be measured objectively or when the work tasks are more difficult (Gottfredson (1997)). Additionally, a well-known finding in the labor economics literature is that IQ tests taken at an early age have strong predictive power for wages later in life, even if the test is taken long before a person's education is complete (*inter alia*, Neal and Johnson (1996), Zax and Rees (2002). For example, as we see below, Zax and Rees find that high school IQ scores have a larger impact on wages when a worker is in his fifties than when the same worker is in his thirties. And as I demonstrate below, the link between cognitive ability and wages is an extremely robust finding among labor econometricians.

In the last two decades, psychologists have started to investigate how IQ is correlated with brain activity. To give one example: An experimenter flashes a bright light in front of a subject's eyes and measures the speed with which that message is conducted to the vision centers at the back of the brain. This simple measure of nerve conduction velocity is correlated +0.37 with IQ after correction for restriction of range (Jensen (1998), 160ff).

Another example: IQ is correlated by between –0.7 and –0.8 with cerebral glucose metabolism (Haier, (1993), Jensen (1998) 157ff). This sugar-burning process is measured using a PET scan while the test subject is trying to answer the most difficult questions on the IQ test. This implies a quite astonishing result: Lower-IQ individuals are generally trying harder than higher-IQ individuals to solve the hard questions. If one believed that IQ differences across individuals were largely driven by social norms in favor of "trying hard" in some groups but not in others, one would expect a positive correlation between IQ and cerebral glucose metabolism. The nerve conduction velocity results and the cerebral glucose metabolism results both support the view that high-IQ individuals have brains that are, on average, more efficient processors of information.

The possibility of studying a key determinant of productivity through brain imaging has important consequences for economists. As microeconomists and financial economists have begun to use brain imaging techniques to study individual decisionmaking--creating the new field of neuroeconomics--it may be time for macroeconomists and productivity researchers to consider similar methods.

One can repeat a number of other examples where objective brain measures are correlated with IQ tests; Jensen (1998, 150-165) is especially useful in this regard. However, these brain activity measures have not to my knowledge been conducted in poor countries, so they shed limited light on whether IQ comparisons from across countries are measuring the same differences that have been found within countries.

Thus, I turn to the Jensen Box. Jensen created a simple test of information processing speed that has been widely used by psychologists interested in intelligence testing. The Jensen box has a home button and between 1 and 8 buttons with lights. Initially, all of the buttons with lights are turned off. When one of the buttons with lights turns on, the test subject takes her finger off the home button and presses the lighted button as quickly as possible. One might expect that this skill is uncorrelated with IQ, but in fact button-pressing speed (known as reaction time) is correlated by an average of –0.35 (Jensen (1998), 204). The correlation is higher when there are more buttons to choose from.

Again, one might believe that this correlation simply results from social norms and acculturation: People who try harder on IQ tests might also be people who try harder on button-pressing tests. But if that is the case, it is difficult to explain the following fact: The correlation between reaction time and IQ derives almost entirely from the speed with which one lifts one's finger from the home button (a measure known as decision time). There is little if any correlation between movement time (the time between finger removal and the time when the lighted button is depressed) and IQ (Jensen (1998), 211-214, 230-231, 242). Again, IQ seems to be correlated with information processing speed (For another review of Jensen Box research, see Deary (2003)).

A natural question is whether this strong correlation between decision time and IQ holds outside the United States. Psychologist Richard Lynn and his coauthors conducted a series of studies in the U.S., Britain, Ireland, Japan, and South Africa to see if the correlation between IQ and decision time held across these countries (reviewed in Lynn and Vanhanen (2002), 66ff). In studies of hundreds of 9-year olds using non-verbal IQ tests, they found that it did. Aggregating to one observation per country, the correlation between national average IQ and national average decision time was always greater than 0.89, regardless of the type of Jensen Box test. The Jensen Box thus appears to verify the value of IQ tests as a measure of information processing speed, a factor that seems likely to influence worker productivity.

This brings us to the question of cross-cultural and nonverbal IQ tests. Because IQ tests are in such demand among educators, businesses, and governments around the world, psychologists have responded by supplying a wide variety of such tests. When a new test is created, its validity is verified by giving both the new and the old test to the same group of people. Further, since the early 1970's, psychologists have responded aggressively to claims that IQ tests were culturally biased in favor of affluent people of European descent. Since the 1980's, there have been no noticeable differences in the validity of IQ tests across racial groups in the U.S. That is, these tests predict non-test outcomes equally well across groups. While we cannot survey this culture-bias question in depth, Jensen ((1998), 360-369) can point the interested reader toward much of the relevant literature.

Of course, one often wants to give IQ tests to children, people who have not learned to read, and people for whom IQ tests do not exist in their language. Non-verbal IQ tests are widely used, such as Catell's Culture-Fair test, Raven's Progressive Matrices, and the Draw-A-Man test. Let us consider the Raven test, since its matrices are a statistically powerful predictor of overall IQ scores, and since similar matrices are part of a conventional IQ test. One is given three visual objects with something in common--a triangle, a square, and a pentagon, perhaps--and is given a set of choices that can complete the pattern--four objects, one of which is a hexagon. The patterns one is looking for may include colors, straight lines, complex designs, and the like. For a literate person, scores on the matrices section are heavily correlated with overall IQ as measured via a traditional test--indeed, scores on these matrix-style tests often have the highest correlation with overall mental ability (*inter alia*, Jensen, (1998), 34-38). Thus, if one had to choose just one portion of an IQ test to give, the matrices section would be a reasonable choice. Accordingly, non-verbal IQ tests such as the Raven play a central role in modern IQ testing.

This completes our brief survey of the validity of cross-cultural IQ tests. For the reader interested in the overall validity of IQ tests, Jensen (1998) is highly recommended, as is Lynn and Vanhanen (2002, c. 6) on the question of the cross-national validity of IQ tests.

Environmental Effects on IQ

All major psychological researchers agree that the environment has a major impact on a person's IQ. And while social forces are an important part of a person's environment, "environment" encompasses far more than just social forces. Factors such as childhood caloric intake, lead and mercury exposure, micronutrient levels, and prenatal maternal health can all have sizeable impacts on IQ.

Leading economists have been convinced of the impact of health and nutrition on IQ. The Copenhagen Consensus project--a panel of prominent economists that included three Nobel laureates--evaluated the costs and benefits of various proposals to improve the well-being of the world's poor (Lomborg (2004)). Their second-highest-ranked recommendation was to include key micronutrients--vitamin and mineral supplements--in the food supply of the world's poorest countries. The impact of nutrition on IQ figured prominently in the arguments in favor the micronutrient policy.

For example, the "challenge paper" on health and nutrition that was presented to the Consensus panelists points to research showing that low-birth-weight babies have IQ's that are roughly 7 points lower than that of full-weight children (Behrman et al., 2004). They also point to research showing that iodine deficiency can reduce IQ by 13.5 IQ points, and that iron deficiency can reduce IQ by 7.5 points. Overall, Behrman et al.'s paper to the Copenhagen Consensus panel had 54 references to the word "cognitive" and 10 references to "IQ." The prominence of IQ in their micronutrient challenge paper and the high ranking given to the micronutrient initiative by the Copenhagen Consensus participants demonstrate that leading thinkers are convinced that the brain health of the world's poorest people is a substantial "barrier to riches" in the sense of Parente and Prescott (2004).

In addition, lead poisoning is a well-known cause of lower IQ's in the U.S., but this is also a problem around the world, particularly in Africa, where leaded gasoline is still widely used (Lacey (2004)). As the Global Lead Network (2005) notes, "Africa is more severely affected by lead poisoning and pollution than any other region of the world. Virtually all countries on the continent still use leaded gasoline in opposition to global trends - and the lead content of that gasoline is the highest in the world."

The possible impact of education on IQ should be noted: While estimates of education's impact on IQ vary, Winship and Korenman (1997) survey the literature of U.S. and Scandanavian studies—which include some natural experiments—and also perform their own analyses of the U.S. National Longitudinal Surveys of Youth. An additional year of education is estimated to raise IQ by anywhere from 1.0 to 4.2 IQ points according to their literature survey. In their own regressions, point estimates range from 1.8 to 2.7 IQ points per year of education depending on the specification. Neal and Johnson (1996), using quarter-of-birth as an instrument for exogenous education, find estimates toward the upper end of these ranges. So the malleability of IQ through education appears to be an important channel for raising national average IQ.

This just touches on the massive literature demonstrating how environmental forces can impact national average IQ. For further references on the effects of the environment on IQ, Jensen (1998, pps 489-509), Sternberg and Grigorenko (2001), and Armor (2003) are especially useful. This body of literature gives hope that the large IQ differences that exist between countries can be narrowed in the future through environmental improvements.

IQ in the Production Function

To begin a discussion of IQ in the Ramsey model, I begin by assuming an IQ-augmented Cobb-Douglas production function,

$$Y_i = e^{\gamma IQ_i} K_i^{\alpha} (A_{it} L_i)^{1-\alpha}$$

The subscript *i* is the country subscript, and γ is the semi-elasticity of output with respect to IQ (Since my concern is with steady-states, I suppress time subscripts wherever possible). Below, I show that the labor economics literature implies precisely this form for the role of IQ in the production function. Note that national average IQ is implicitly a component of total factor productivity.

As in Mankiw, Romer, and Weil (1992) I assume that $\ln(A_{it}) = \bar{a} + gt + \varepsilon_i$, implying a one-time country-specific shock to the level of technology; *gt* represents the time trend in technology assumed constant across all countries. Mankiw et al. assume that ε_i was uncorrelated with any other parameter in the model; I relax this assumption by assuming only that ε_i has mean zero and is possibly correlated with IQ. Thus, all countries have access to the same global stock of knowledge, plus or minus a country-specific shock to the level of technology.

Since in competitive markets (without externalities) labor and capital earn their marginal products, this model implies that (suppressing subscripts):

$$\text{Real wage} = \frac{\partial Y}{\partial L} = (1-\alpha) e^{\gamma IQ} \left(\frac{K}{L}\right)^{\alpha} A^{1-\alpha}$$

$$\text{Interest Rate} = \frac{\partial Y}{\partial K} = \alpha e^{\gamma IQ}\left(\frac{K}{AL}\right)^{\alpha} \quad (1)$$

In this section, it is the real wage that concerns us. I take logs and simplify:

$$\text{Log(Real wage)} = \log[e^{\gamma IQ}] + \log[(1-\alpha)\left(\frac{K}{L}\right)^{\alpha} A^{1-\alpha}]$$

$$= \gamma IQ + \log[(1-\alpha)\left(\frac{K}{L}\right)^{\alpha} A^{1-\alpha}] \quad (2)$$

The first term of equation (2) notes that a one-point increase in IQ raises the real wage by γ percent. Fortunately for our purposes, there is large literature in labor economics devoted to estimating γ: The exogenous impact of a rise in IQ (often referred to as cognitive ability) on the log of real wages. I survey this literature below.

In light of equation (2), I can now explain why I allow the possibility of a correlation between A (often thought of as disembodied technology) and IQ. The focus of this paper is on one particular channel through which IQ impacts output per worker: by raising the private marginal product of labor. IQ surely impacts productivity through other channels—human capital spillovers come immediately to mind, and it seems quite plausible that the level of IQ has important impacts on the rate of technological innovation and technology adoption.

Further, the relationship may run in exactly the opposite direction: From higher productivity to higher IQ, perhaps by way of better nutrition, more stimulating educational environments, and the like. The productivity-to-IQ causal chain should be kept in mind as a real possibility, since rich countries tend to have healthier, better-educated populations: these would be just the types of populations that would be expected to perform well on IQ tests. Our simple calibration exercise allows us to separate out the γ impact (of IQ on output via worker productivity) from any other possible channel through which IQ and productivity could be related.

Therefore, one should keep in mind that of the many possible reasons for the high unconditional correlation (0.82) between national average IQ and log worker productivity, I explore only one possible channel in this paper. If this strong relationship cannot be explained by the channel running from IQ to the private marginal product of labor, then further avenues will need to be explored.

The IQ-augmented Ramsey model

While the same results will obtain whether I use a Ramsey or a Solow growth model, I use the Ramsey model. I assume that aside from differences in IQ and A (the technology parameter), all countries share the same parameter values. Assume the consumer's utility function is

$$V = \sum_{t=0}^{\infty}\left(\frac{1}{1+\rho}\right)^{t} c_t^{1-\theta}$$

If depreciation rate = δ, it can be shown that in steady-state:

$$\frac{\partial Y}{\partial K} = \rho + \theta g + \delta$$

(For all Ramsey-related proofs, see, *inter alia*, chapter 2 of Barro and Sala-i-Martin (2004)). This result implies that the interest rate and the capital per effective labor ratio are determined by the model's deep parameters, ρ, θ, g, and δ. Combining this result with (1) and simplifying yields:

$$\left(\frac{K}{L}\right)^{ss} = A\left(\frac{\alpha e^{\gamma IQ}}{\rho + \theta g + \delta}\right)^{\frac{1}{1-\alpha}}$$

Note that when IQ is higher, steady-state capital per worker is also higher. This is because a rise in IQ causes a higher non-steady-state interest rate, which generates more saving. This in turn generates more capital per worker in the new steady-state.

My original IQ-augmented production function can be rewritten as:

$$\left(\frac{Y}{L}\right) = A^{1-\alpha} e^{\gamma IQ} \left(\frac{K}{L}\right)^{\alpha}$$

Plugging in steady-state K/L and simplifying yields:

$$\left(\frac{Y}{L}\right) = A e^{\left(\frac{1}{1-\alpha}\right)\gamma IQ} \left(\frac{\alpha}{\rho + \theta g + \delta}\right)^{\frac{\alpha}{1-\alpha}}$$

Taking logs, substituting out the technology expression *A*, and combining constants into the term μ yields

$$\log\left(\frac{Y}{L}\right)^{ss} = \frac{\gamma}{1-\alpha} IQ + \mu + gt + \varepsilon_i \qquad (3)$$

This is the equation I use to evaluate the impact of IQ differences on steady-state living standards. The $\gamma/(1-\alpha)$ coefficient captures one unique channel through which IQ impacts living standards: by raising the private marginal product of labor and hence steady-state productivity. As noted above, the error term may well be correlated with a nation's IQ, and captures any other channel that could explain IQ's correlation with output per worker.[1]

[1]Note that since the parameters relating to the steady-state interest rate are assumed to be the same across countries, this implies that whether each economy is open or closed to capital flows will have no impact on the steady-state capital stock.

Data and Parameters

Two key parameters are needed for our simple calibration exercise: the semi-elasticity of wages with respect to IQ, and the elasticity of output with respect to capital. I discuss these in order.

Labor economists have a rich literature estimating the link between cognitive ability and wages. In most cases, the cognitive ability measure is the Armed Forces Qualifying Test (AFQT) given as part of the National Longitudinal Survey of Youth. The AFQT is the test used to measure of cognitive ability in Murray and Herrnstein's *The Bell Curve*, in Neal and Johnson (1996), and in Cawley et al. (1997).

In the labor economics literature, differences in cognitive ability are usually reported as z-scores, that is, as standard deviations away from the mean. However, in the spirit of tying the economics literature closer to the psychology literature, and also to aid interpretation when comparing results from different countries, I will make the necessary conversions in order to report all cognitive scores in terms of IQ points.

As is well known, the mean IQ in the U.S. is typically defined as equal to 100, and the standard deviation of I.Q. in the U.S. population is defined as equal to 15. And this standard deviation of 15 holds in practice: For example, when Zax and Rees (2002) analyzed an actual IQ test given to citizens of Wisconsin, they found the standard deviation of their sample was 15.1. Thus, γ equals one-fifteenth of the estimated effect of a one-standard-deviation rise in cognitive ability on wages.

The labor economics literature has used a variety of innovative techniques to estimate the impact of a rise in cognitive ability on wages. Many studies control for a wide variety of variables, such as education, age, and sector of employment. Others use innovative instruments, such as Neal and Johnson (1996) who used quarter of birth as an instrument for exogenous changes in education (and hence, to estimate the effect of exogenous changes in education on IQ). When assessing the vast literature on cognitive ability and wages, I put more weight on estimates that have been widely cited and that appear to use the best econometric techniques.

A crucial question is that of appropriate controls: As Zax and Rees (2002) carefully show, the decision to include education variables in an regression of wages on IQ could bias the IQ coefficient downward. For example, if higher IQ causes more education, then some of the IQ coefficient's true value would be transferred to the education coefficient. Thus, the simplest regressions may well be the best ones for our purposes. This implies that I should place some weight on results from naïve bivariate regressions of wages on IQ when trying to estimate the true value of γ.

Using a number of controls, Neal and Johnson (1996) estimate γ=1.17, while Bishop (1989) estimates γ=1.27. In regressions that omit non-cognitive control variables, Cawley et al. (1997) find a range of estimates across various racial and gender categories, ranging from γ =1.3 for black females to γ=1.0 for white males. When controls are added to the Heckman results, the estimates drop by between one-third to one-half. When Zax and Rees omit non-cognitive control variables, their estimates are γ=0.7 for males age 35 and γ= 1.4 for males in at age 53; they consider these to be upper bounds for the true estimate. When Zax and Rees include controls, the estimates drop to 0.3 and 0.7, respectively.

In one literature survey that looks at 65 estimates of γ without regard to the quality of the econometric methodology, Bowles et al (2001) find an average estimate of

γ=0.5 over the past four decades, an estimate that has a wide variance but no substantial time trend. The discovery of no trend provides some reason to believe that γ remains relatively stable as nations become richer. The one exception to their no-trend result is a rising trend in γ among African Americans (p.23).

The question of whether γ is roughly similar across countries should be briefly discussed. Within the U.S., Cawley et al. (1997) test for and reject the restriction that γ is equal across gender and racial groups. Their finding that white men's wages are less responsive to IQ than any other demographic group (aside from Hispanic men) provides some preliminary evidence that the wage-IQ link will be at least as strong in poorer countries as it is in the U.S.

Behrman et al. (2004) survey the academic literature on estimates of γ from various developing countries. They report values for Pakistan ($\gamma\approx0.87$), Ghana (0.67), Kenya (1.07), Tanzania (0.67), Columbia (0.47 to 1.53), and Chile (0.4 to 0.67). If I average the Columbia and Chile estimates to create one estimate per country, then the overall mean for these 6 countries is $\gamma\approx0.8$, with a median of 0.77.

I summarize this wide variety of estimates by taking γ=1 as the preferred estimate. In part, this is because U.S. estimates using modern methodologies rarely find $\gamma<1$, and generally find $\gamma>1$. This is also because if I average the median developing country estimate of $\gamma\approx0.8$ with the $\gamma\approx1.2$ found in the U.S. by Neal and Johnson (1996) and Bishop (1989), I arrive at an average of γ=1. As a robustness check, I also consider γ=1.25 and γ=0.5 as alternative estimates.[2]

[2] In a footnote below, I consider the possibility that γ depends on a nation's level of development. Such an assumption improves the calibration's fit.

Now I turn to α, the capital elasticity of output. A conventional estimate of α based on the share of income paid to owners of physical capital would be one-third (*inter alia,* Gollin, 2002). However, there are good reasons to believe that α is substantially larger than that. A basic result in the growth literature is that α is a key determinant of the speech with which an economy converges to its steady-state growth path: The greater the α, the more rapidly capital is accumulated, and the greater is the speed of convergence. Barro and Sala-i-Martin (2004, 110, 496) note that countries (as well as U.S. states and Japanese prefectures) converge to the steady state growth path much too quickly for a value of α as small as one-third. They find that $\alpha=0.75$ fits the convergence data much better.

Such a large value for α could be due to the important role played by the accumulation of human capital by way of education, as Mankiw, Romer, and Weil (1992) argue. They find that a human-capital augmented Solow model with a coefficient on education-based human capital equal to one-third fits the data well; when they combine this with a physical capital elasticity of one-third, this implies an aggregate model where $\alpha=0.67$.

By contrast, Parente and Prescott (2000, 2004) argue that the key form of "missing capital" is organizational capital. Investment in organizational capital includes activities such as "starting up a new business, learning-on-the-job, training, education, research and development, and some forms of advertising" (p. 49; note that education is among their forms of missing capital). This unmeasured investment ranges from 35% to 55% of GDP, according to Parente and Prescott (2004). In their attempt to match the rapid catch-up of the East Asian economies, they conclude that "capital share values in the range from 0.55 to 0.65 are consistent with the growth miracles" (p. 47).

Thus, if I am trying to explain why some countries are richer than others, an α=0.33 is likely to miss the important roles of human and organizational capital. I use α=0.33, 0.5, and 0.75, but prefer the latter two estimates.

Our data sources should briefly be mentioned. As noted above, our national average IQ estimates are from Lynn and Vanhanen (2002). Our GDP per worker estimates are from the Penn World Tables. In total, I have complete data for 63 XXX 67 countries that are broadly representative of the world's economies. Data and software are available upon request.

Using the Model

In this section, I combine the steady state equation of the IQ-augmented Ramsey model with conventional parameter values for γ and α to illustrate how IQ differences can have a large impact on steady-state living standards. Consider two countries that differ only in average IQ. The ratio of steady-state living standards in these two countries would then be:

$$\frac{(Y/L)_{hi}^{ss}}{(Y/L)_{lo}^{ss}} = e^{\frac{\gamma}{1-\alpha}\Delta IQ} \qquad (4)$$

where ΔIQ is the difference in IQ between the two countries. Lynn and Vanhanen show that if countries are ranked according to IQ, then the bottom decile has a median IQ of 66 and the top decile has a median IQ of 104. I take γ =1 as our preferred estimate; under this assumption a rise of 1 IQ point raises wages (and the marginal product of labor) by a modest 1%.

Therefore, as Figure 2 illustrates, if a country moved from the bottom IQ decile to the top IQ decile (a rise of 38 points), steady state living standards would be 1.75 times the initial value if α=1/3, and 4.5 times the initial value if α=3/4. In either case, IQ's impact on steady-state living standards would be too large too ignore.

But perhaps our estimates of cross-country IQ differences are exaggerated. If the true IQ gap between the top 10% and the bottom 10% is only half of Lynn and Vanhanen's estimate--19 points--then a move from bottom to top would imply a rise in steady state living standards of between 33% and 110%, depending on the value of α.

The implications are clear: If Lynn and Vanhanen are correct in concluding that IQ differences across countries are substantial, and if labor economists are correct in believing that higher IQ raises the marginal product of labor, then the IQ-augmented Ramsey model implies that IQ is an important determinant of cross-country income differences. This result holds even if one believes that Lynn and Vanhanen's dataset inaccurately measures national average IQ for particular countries: Large between-country IQ differences are all that is needed to reach this result. Whether the role of IQ is overwhelming or merely substantial turns on the preferred value of α.

I should note the results in this section do not depend on IQ being exogenous. I demonstrate below that reverse causality is unlikely to be the main explanation for the strong empirical IQ-productivity relationship. However, even if reverse causality *were* important, the above results would still hold, since microeconomic studies demonstrate convincingly that IQ has an independent impact on the marginal product of labor.

So if the actual causal chain starts with a high level of disembodied technology (A) causing higher output per worker, which in turn causes higher IQ, it is difficult to believe that the causal chain stops there. According to economic theory, the chain continues to a second set of links, where higher IQ-workers cause more productivity and hence cause a higher steady-state capital stock. This paper is concerned only with that second set of links. Whether the first set of links is as strong as the second remains to be demonstrated.

Calibration Results

Our calibration exercise is quite straightforward: In a regression of log output per worker on IQ, I impose a variety of estimates for the $\gamma/(1-\alpha)$ coefficient, and I report the accompanying R^2. The resulting R^2 is the percentage of cross-country income variance that can be explained through a single channel: the steady-state impact of mean IQ differences on the marginal product of labor.

The only coefficient estimated in this regression is the constant; there are no free parameters to speak of. For reference, I note that the R^2 between log GDP per worker in 2000 and Lynn and Vanhanen's national average IQ estimate is 64%, and in an OLS regression, 1 IQ point is associated with 7.2% higher GDP per worker.

Results are reported in Table 1.[3] For our preferred estimate of γ=1.0, IQ can explain between 24 and 52 percent of cross-country income variation depending on the choice of α. Therefore, IQ's impact on wages would explain between 38% (i.e., 24%/64%) and 81% of the relationship between IQ and living standards.

If, instead, IQ has a 25% larger impact on wages (γ=1.25), and if Barro and Sala-i-Martin are correct in their estimate of the "broad capital" share (α=.75), then IQ's effect

[3] Results were substantially unchanged if 2000 log GDP per person was used instead of log GDP per worker.

on wages can explain 91% (=58%/64%) of the IQ/living standards relationship. In such a case, there would be little need to invoke human capital externalities, reverse causation, or other factors in explaining the strong relationship between IQ and GDP per worker.

And even if γ=0.5--half of our preferred estimate--IQ's impact on wages explains at least one-eighth and certainly more than one-fourth of cross-country income variation. So even under the most restrictive assumptions, IQ's impact on wages appears to belong on any top ten list of explanations for cross-country income differences.[4]

Note that in each of these cases, the coefficient $\gamma/(1-\alpha)$ is always less than the 7.2 that would occur in an OLS regression; for example, in the γ=1 case, the relevant values for α=1/3, 1/2, and 3/4, are 1.33, 2, and 4, respectively. Therefore, in no case does the IQ-augmented Ramsey model overpredict the relationship between IQ and steady-state productivity per worker: more remains to be explained. We now turn to one possible explanation.

[4] I also considered the possibility that a nation's γ rises as that nation's national average IQ rises. This would be the case, if, for instance, countries are better at sorting workers into more-productive jobs as the national average IQ rises. In particular, I considered the following functional form: $\gamma = 0.8 + 0.0133(IQ-70)$. This would be the appropriate form if moving from the bottom to the top of the global distribution of IQ raised gamma from 0.8 to 1.2, and is equivalent to adding a quadratic term to the linear model of equation (3). The 0.8 value is the mean γ for developing countries, while the 1.2 value is close to many of the U.S. estimates noted in the text.

Such a model fits the data better than the results reported here. In the case of year 2000 GDP per worker, values of α=1/3, 1/2, and 3/4 explain 44%, 54%, and 63%, respectively, of the variance in the global income distribution. This improved fit is robust to changes in the intercepts of the γ equation. The improved fit is not surprising, but it is not tautological. It is not surprising since this endogenous γ equation will tend to depress estimated steady-state productivity in lower-IQ countries and raise it in higher-IQ countries--thus widening the global income distribution. And as noted in the text, the model implied by equation (3) underpredicts the empirical relationship between IQ and living standards. But the improved fit is not tautological: Since there are no free parameters to speak of in the calibration exercises, adding a quadratic term to the calibration will not necessarily improve the model's fit.

Despite the improved fit that results from endogenizing γ in this way, I choose to impose a single value for γ. I do so largely because the growth and labor literatures have, to my knowledge, done no theoretical or empirical work on the appropriate functional form for γ. Since I intend to remain close to the mainstream of these literatures, I leave the question of γ's functional form to future research.

Addressing Reverse Causality

As the previous section demonstrates, if α is set equal to Barro and Sala-i-Martin's preferred value of 0.75, and γ is equal to (or even slightly less than) the preferred values of Neal and Johnson or Bishop, then the IQ-wage channel (in steady-state) appears to be able to explain the vast majority of the IQ-productivity relationship. In such a case, there is little need to invoke reverse causality, human capital spillovers, or the effect of IQ on technological innovation to explain the correlation of 0.74 between IQ and log output per worker.

But perhaps the true values of α and γ are smaller: in such a case, there could be an important role for these other channels. While I leave most of these questions to future research, I will take a moment to address one key question: Whether a dramatic rise in GDP per worker causes a dramatic rise in national average IQ.

The region of the world that has witnessed the most rapid increases in living standards the world has ever known is unambiguously East Asia. Surely, this region would be an ideal testing ground for the productivity-causes-IQ hypothesis. If most of the IQ-productivity relationship were reverse causality, then I would expect to see the East Asian economies starting off with low IQ's in the middle of the 20th century, IQ's that would rapidly rise in later decades, perhaps even converging to European IQ levels.

But what would I expect the mid-20th-century starting point for IQ to be? Perhaps I should assume that it would be as low as the bottom decile of the global IQ distribution which has a mean of 66, as noted above. That would place such countries more than two standard deviations below the mean IQ within the United States. Or perhaps that assumption is too strong; at the very least, I would expect these poor East Asian economies to have started off with IQ's below the unweighted global mean of 90, and certainly well below the U.K and U.S., which are within a point or two of 100.

However, this is not the case. When Sailer (2004) employs Lynn and Vanhanen's raw IQ data--based on 183 tests taken over the past 100 years--to create a panel dataset, he reports that average East Asian IQ's were *never* estimated below 100 before the 1980's (Figure 3). From the 1950's and 60's, for example, Lynn and Vanhanen have four IQ tests based on relatively large samples: Two from Japan (1951 and 1967), one from Taiwan (1956, only a few years after the Nationalists were driven there from the mainland), and one from Hong Kong (1968).

Lynn and Vanahen's data from rapidly growing economies in Southeast Asia, though based on only five observations, support a similar conclusion:

Indonesia, 1959:	IQ = 89
Phillipines, 1970:	IQ= 86
Singapore, 1974:	IQ = 103
Thailand, 1987:	IQ = 91
Malaysia, 1992:	IQ = 92

Average IQ's start about ten points lower than in East Asia, but also end about ten points lower. There have apparently been no twenty-to-thirty-point IQ increases in Southeast Asia as these countries began to emerge from dire poverty.[5]

But IQ increases do occur on a national scale. Indeed, there is a large literature in psychology that studies the rise in IQ's across the developed world, a rise of roughly two to three points per decade across most of the 20th century. This phenomenon is known as the Flynn effect (after Flynn (1987)), and it has been widely studied and widely debated. Explanations that psychologists have considered for the Flynn effect include better

[5] The reader interested in further exploring changes in IQ scores over time for a particular country or region is urged to consult Appendix 2 of Lynn and Vanhanen (2002) or Sailer's (2004) online spreadsheet.

nutrition, better education, and educational television, as well as the possibility that the Flynn effect is merely a "nominal" rise in narrow test-taking ability with little impact on "real" general reasoning and information processing abilities. For helpful reviews of the Flynn effect literature, Neisser (1998) and Jensen (1998, 318-333) are highly recommended.[6]

Unfortunately, economists have not yet brought their powerful econometric tools to bear on the question of what causes the Flynn effect, either within the U.S. or in other countries. As economists come to recognize the importance of IQ differences for determining living standards, one can only hope that they will devote substantial resources to determining what causes the Flynn effect within the developed world, as well as whether policy interventions can set off even larger Flynn effects in the world's poorest countries. If economists can collaborate with policymakers to initiate a process of global IQ convergence, they will have removed one of the most substantial barriers to riches.

IQ and Productivity, 1960-1990

One question of interest is whether the IQ-productivity relationship has strengthened or weakened over the past few decades. Shocks such as the Great Depression and the Second World War were likely to move nations away from their steady-state paths; accordingly, one would expect the IQ-productivity relationship to have strengthened since then.

As Table 2 shows, I indeed found this to be the case. I used LV's IQ data along with Penn World Table data for each decade from 1960 through 1990 (1950 only had 38

[6] For evidence of a large Flynn effect in rural Kenya in recent decades, see Daley et. al (2003).

relevant observations, and so is omitted). As before, equation (3) was used to estimate the IQ-productivity relationship, while the IQ-elasticity of wages is assumed to equal 1 for simplicity. Both the unconditional R^2 and the fraction of the variance explained by the IQ-wage relationship increase steadily across the decades. This is true regardless of the capital share parameter in question.

This increasing relevance of IQ could be due to a number of factors. Perhaps as other differences across countries diminish—as market-oriented institutions take hold and as knowledge of science, technology, and management methods diffuse across countries—then IQ differences have become increasingly important. Another possibility is that modern economies depend much more on cognitive ability than they once did. The simplest possibility would be the one with which I began this section: that the crises of the early and middle 20th century pushed many nations away from their steady-state growth paths, paths toward which they are approaching every year.

IQ as a Missing Input

Based on IQ's power to explain such a large portion of cross-country income differences, it would be reasonable to conclude that IQ is one of the "missing inputs" that Caselli (2004), Easterly (2004), and other growth researchers are looking for. Caselli, for example, considers the possibility that what he calls "schooling quality"—a combination of standardized test scores broadly comparable to IQ—may be a key missing input. However, the conclusions he can draw are limited by the existence of relevant math, science, and reading scores from only 28 countries.

IQ data, by contrast, are much more widely available: Lynn and Vanhanen's data cover 81 countries, and IQ measures have the benefit of a massive international literature linking cognitive ability to wage outcomes. Further, there is a rich clinical and academic literature within psychology devoted to making scores from different types of IQ tests comparable. And as Jones and Schneider (2004) demonstrate in their consideration of the Barro-Lee (1993) and Hanushek-Kimko (2000) data on cross-country standardized test scores, such scores are quite strongly correlated with IQ scores, and are likely to be measuring many (though not all) of the same productive mental skills that IQ tests measure.

As an empirical matter, then, the merits of considering IQ as a "missing input" are clear: Widely available data combined with large literatures in labor econometrics and empirical psychology on which growth economists can draw. But what of the possible role for IQ in growth theory? Here, one can not only point to the IQ-augmented Ramsey model presented here; one can also consider the possibility of a new theoretical literature that spells out the ability (or lack thereof) of IQ to explain productivity levels as well as productivity growth rates.

The Ramsey-style model of Manuelli and Seshadri would be a natural example: In their model, ex-ante differences in total factor productivity of at most 27% interact with human capital investment decisions and fertility choices to replicate the current global income distribution. Persistent IQ differences would be a natural source for such ex-ante differences in total factor productivity. Indeed, the current span of global IQ differences—38 points between the bottom and top IQ deciles—creates a TFP gap that is almost double the amount needed in their model.[7]

As an additional example: Warner and Pleeter (2001) find that higher cognitive ability is associated with lower discount rates. If these results generalize across countries, then IQ may impact steady-state capital accumulation through yet another channel: via country-specific differences in discount rates.[8] And the possible links between national average IQ and technology innovation and adoption are too obvious to belabor.

One can multiply examples, but the point is clear: stylized facts related to IQ and productivity are ready and waiting for the theorist who seeks to explain a large part of the puzzle of cross-country productivity differences. Accordingly, IQ may play an important role in answering Prescott's (1998) call for a theory of total factor productivity.

Conclusion

The wide divergence we see in living standards across countries is not a puzzle: This divergence is precisely what quantitative general equilibrium theory predicts as long as there are large, persistent differences in general reasoning ability across countries.

However, the differences in living standards we see in the real world are even larger than the differences predicted by the IQ-augmented Ramsey model. According to the model presented here, countries in the top IQ decile should be, at most, 4.5 times

[7] Note that if $\gamma=1$, then $\exp(.01*38)=1.46$; so a 38-point IQ gap would cause a 46 percent TFP gap.
[8] Indeed, persistent cross-country differences in average cognitive ability could provide a solution to the Feldstein-Horioka (1980) international savings puzzle: High-IQ countries would be both more productive (hence creating a higher demand for investment goods) and more patient (hence creating more private savings with which to meet that demand). Experimental findings of the strong relationship between cognitive ability and patience can be found in Benjamin and Shapiro (2005).

more productive than countries in the lowest IQ decile. However, productivity between such countries instead differs by a factor of roughly 20. Another way to phrase this result is that if the IQ-wage channel were the only important mechanism driving cross-country income differences, then if today's rich countries are taken to be at the technological frontier, then no country today would be less productive than Thailand, Bulgaria, Guatemala, or Morocco.

Therefore, the desperate poverty of the world's poorest countries is not explained by this model. Indeed, this model makes no claim to being a complete explanation of cross-country differences in living standards. Recall that if one IQ point raises wages by roughly one percent, as many labor economists claim, then this model explains between 26% and 56% of the cross-country variance in output per worker. This means that much remains to be explained by factors such as political institutions, colonial experience (Acemoglu, Johnson, and Robinson (2001)), innovation policy, and many other non-cognitive factors.

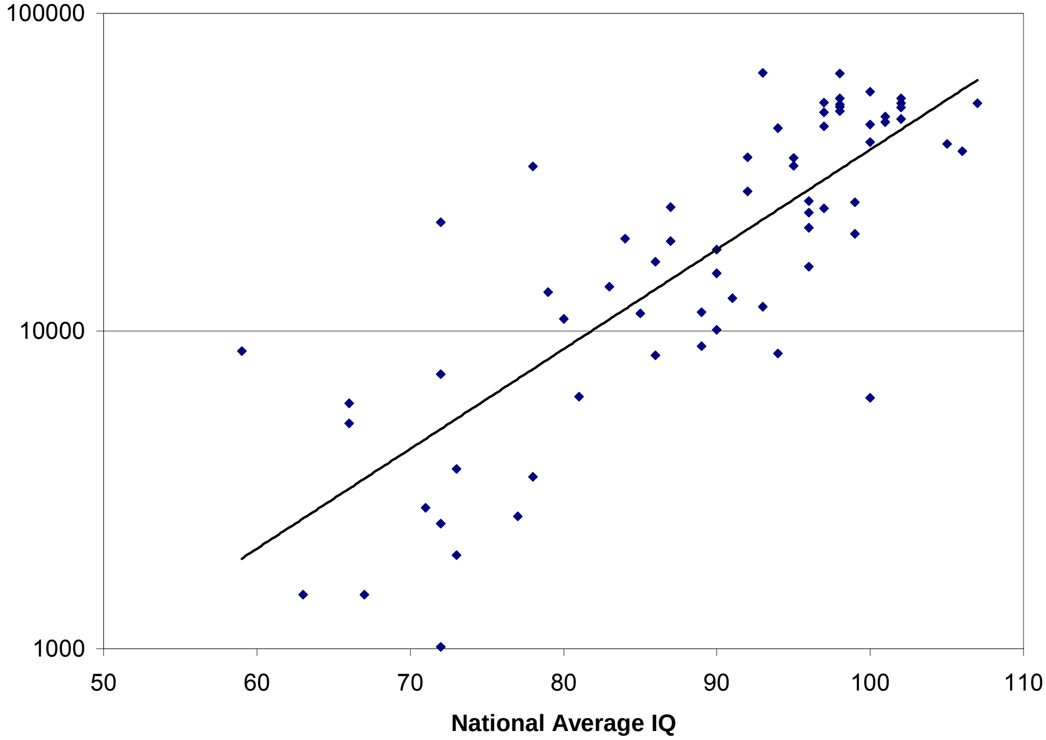
But with that crucial caveat, I close by noting that this paper has uncovered an explanation for productivity differences that has been left entirely unexplored in the literature: the steady-state impact of persistent differences in cognitive ability on the marginal product of labor.

What else have I left unexplained? I have not explained the entire correlation of 0.80 between IQ and worker productivity. Perhaps human capital externalities and feedback effects from worker productivity to IQ are part of the story. Indeed, any non-wage explanation for the IQ-productivity link remains open for exploration.

More importantly, I have not attempted to explain why IQ diverges so much across countries--and diverges even across poor countries. In this respect, these results are similar to those of Kydland and Prescott (1982), who showed that well-documented differences in productivity across time could explain a large fraction of the variance of output. Similarly, I have shown that well-documented differences in IQ across countries can explain a large fraction of the variance of output. And just as Kydland and Prescott left the investigation of the causes of productivity fluctuations to future research, I leave the investigation of the causes of persistent IQ differences to future research.

I hope that economists can bring their powerful econometric tools to bear on the question of why IQ gaps across poor countries are so large. If economists can find ways to close these persistent IQ gaps, the world's poorest citizens may be able to make full use of their productive potential. If growth economists instead avoid studying differences in national average IQ, the results presented here imply that they may be missing more than half the story.

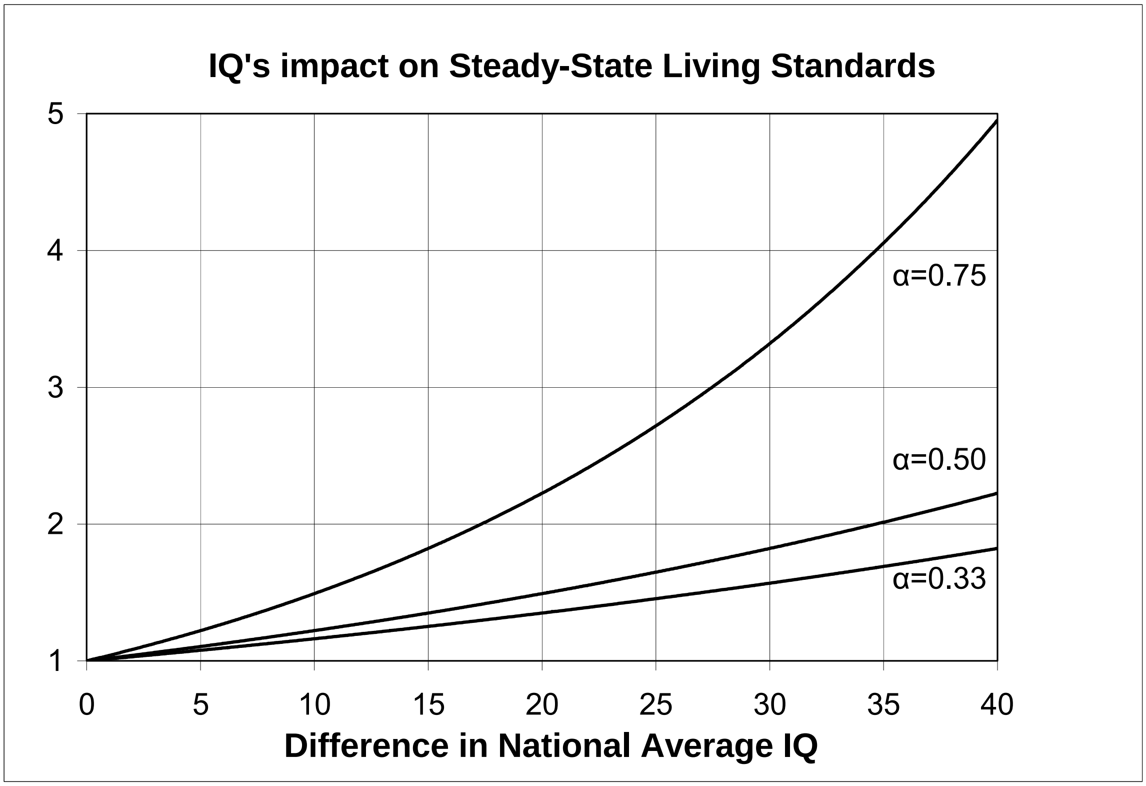
Figure 1: National Average IQ and Year 2000 GDP Per Worker



Notes: Y-axis shows GDP per worker in logarithmic scale. In this bivariate regression, the coefficient on national average IQ is 0.072, and the R^2 is 64%. Thus, a one-point rise in IQ is associated with 7.2% higher output per worker. The outlier in the lower-right corner is China.

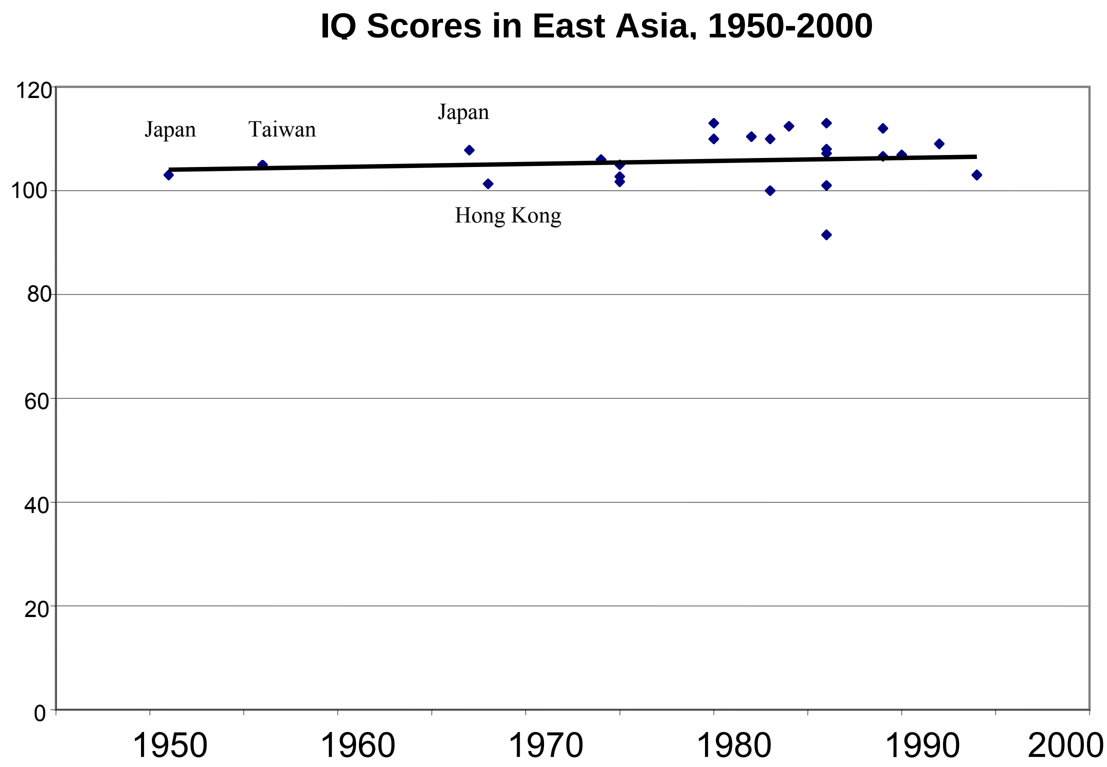
Source: Lynn and Vanhanen (2002) and Penn World Tables 6.1 for IQ and GDP data, respectively.

Figure 2



Notes: The value on the y-axis is $(Y/L)^{SS}_{hi}/(Y/L)^{SS}_{lo}$, the ratio of steady-state living standards in two countries who differ only in national average IQ. This chart is based on equation (4) in the text under the assumption that γ, the semi-elasticity of wages with respect to IQ, equals 1. α is the capital elasticity of output.

Figure 3



Source: Lynn and Vanhanen (2002), as reported in Sailer (2004).

Table 1: Productivity variance explained by IQ's impact on wages

	γ=0.5	γ=1.0	γ=1.25
α=.33	**13%**	**24%**	**29%**
α=.5	**17%**	**31%**	**37%**
α=.75	**31%**	**52%**	**58%**

Notes: γ is the semi-elasticity of output with respect to IQ, and α the capital elasticity of output. The percentages indicate the variance in year 2000 GDP per worker that can be explained by IQ's steady-state impact on the private marginal product of labor, as set forth in equation (3). For reference, the R^2 from simple regression of year 2000 log GDP per worker on national average IQ is 64%. IQ and GDP data are from Figure 1.

Table 2: Productivity variance explained by IQ's impact on wages, 1960-1990

	1960	1970	1980	1990
α=.33	**19%**	**21%**	**22%**	**24%**
α=.5	**24%**	**27%**	**28%**	**31%**
α=.75	**38%**	**43%**	**46%**	**52%**
R^2	**40%**	**48%**	**54%**	**65%**
N	60	62	63	66

Notes: γ, the semi-elasticity of output with respect to IQ, is assumed to be 1, and α is the capital elasticity of output. The percentages indicate the variance in the year's GDP per worker that can be explained by IQ's steady-state impact on the private marginal product of labor, as set forth in equation (3). For reference, the R^2 from simple regression of the year's log GDP per worker on national average IQ is also reported. GDP data is from the Penn World Tables.

Bibliography

Acemoglu, D., Johnson, S. & Robinson, J. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation, *American Economic Review, 91*, 1369-1401.

Armor, D. J. (2003). *Maximizing intelligence*. New Brunswick: Transaction Publishers.

Barro, R. J. and Lee, W. (1993). "International Comparisons of Educational Attainment," *Journal of Monetary Economics*, 32, 363-394. Data available at www.nber.org.

Barro, Robert and Xavier Sala-i-Martin. (2001) *Economic Growth*, 2nd ed.. Cambridge, MA: MIT Press.

Behrman, Jere, Harold Alderman and John Hoddinott. (2004). *Copenhagen Consensus – Challenges and Opportunities: Hunger and Malnutrition*. http://www.copenhagenconsensus.com/Default.asp?ID=223

Benjamin, Daniel J. and Jesse M. Shaprio, "Does Cognitive Ability Reduce Psychological Bias?" working paper, Harvard University.

Bils, Mark and Peter Klenow. (2000). "Does Schooling Cause Growth?" *American Economic Review, 90*, 1160-83.

Bishop, John H. (1989). "Is the Test Score Decline Responsible for the Productivity Growth Decline?" American Economic Review, *79*, March, 178-197.

Bowles, Samuel, and Herbert Gintis, and Melissa Osborne (2001). "The Determinants of Earnings: Skills, Preferences, and Schooling," *Journal of Economic Literature*, *39*, 1137–1176.

Cascio, Wayne F. (2003). *Managing Human Resources: Productivity, Quality of Work Life, Profits*, 6th ed. New York: McGraw-Hill Irwin.

Caselli, Francesco (2003) "The Missing Input: Accounting for Cross-Country Income Differences," Harvard University working paper. Forthcoming in *Handbook of Economic Growth.*

Castro, Rui. (2005). "Economic Development and Growth in the World Economy," *Review of Economic Dynamics*, *8*, 1, 195-230.

Cawley, John, Karen Conneely, James Heckman, and Edward Vytlacil. (1997). "Cognitive Ability, Wages, and Meritocracy," in Bernie Devlin, Stephen E. Fienber, Daniel P. Resnick, and Kathryn Roeder, *Intelligence, Genes, and Success: Scientists Respond to* The Bell Curve. New York: Springer-Verlag.

Daley, T. C., Whaley, S. E., Sigman, M. D., Espinosa, M. P., Neumann, C. (2003). IQ on the rise: The Flynn effect in rural Kenyan children, *Psychological Science, 14*, 215-219.

Deary , I. J. (2003) Reaction time and psychometric intelligence: Jensen's contributions, In H. Nyborg (Ed.), *The scientific study of general intelligence: Tribute to Arthur R. Jensen* (pp. 53-75). Amsterdam: Pergamon.

Easterly, William (2004). "Globalization, Poverty, and All That: Factor Endowment versus Productivity Views." Working paper, NBER Globalization and Poverty Workshop.

Feldstein, Martin and Horioka, Charles. (1980). "Domestic Saving and International Capital Flows." *The Economic Journal*, *90*, June, 314-329.

Flynn, J. R. (1987). Massive IQ gains in 14 nations, *Psychological Bulletin, 101*, 171-191.

Global Lead Network, (2005). "Leaded Gasoline Phase-Out in Africa." www.globalleadnet.org/policy_leg/policy/africa.cfm
Gollin, Douglas. (2002) "Getting Income Shares Right," *Journal of Political Economy*, *110*, 2, 458-474.
Gottfredson, Linda. (1997). "Why g matters: The complexity of everyday life," *Intelligence, 24,* 79-132.
Haier, Richard J. (1993). "Cerebral glucose metabolism and intelligence," in Philip A. Vernon (Ed.), *Biological Approaches to the Study of Human Intelligence*, Norwood, NJ: Ablex, 313-373.
Hanushek, E. & Kimko, D. (2000). "Schooling, Labor Force Quality, and the Growth of Nations," *American Economic Review*, 90, 1184-1208.
Herrnstein, Richard and Charles Murray. (1994). *The Bell Curve: Intelligence and Class Structure in American Life.* New York: Free Press.
Heston, Alan, Robert Summers and Bettina Aten, (2002). *Penn World Table Version 6.1*, Center for International Comparisons at the University of Pennsylvania (CICUP), October 2002.
Jensen, Arthur R. (1998). *The g factor: The science of mental ability*. Westport, CT: Praeger.
Jones, Garett and W. Joel Schneider. (2004). "Intelligence, Human Capital, and Economic Growth: An Extreme-Bounds Analysis." Working Paper, Southern Illinois University Edwardsville.
Kydland, Finn E and Edward C. Prescott. (1982). "Time to Build and Aggregate Fluctuations," *Econometrica*, *50*, 6, 1345-70.
Lacey, Marc. (2004) "Belatedly, Africa is Converting to Lead-Free Gasoline," *New York Times*, October 31.
Lomborg, Bjorn., ed. (2004). *Global Crises, Global Solutions.* New York: Cambridge UP.
Lynn, Richard and Tatu Vanhanen. (2002). *IQ and the Wealth of Nations.* Westport, CT: Praeger Publishers.
Mankiw, N. Gregory., David Romer, and David Weil. (1992). "A Contribution to the Empirics of Economic Growth," *Quarterly Journal of Economics, 107*, 407-38.
Neal, Derek A. and William R. Johnson. (1996). "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, *104*, 5, 869-895.
Nechyba, Thomas (2004). *Review of* IQ and the Wealth of Nations, *Journal of Economic Literature*, *42, March,* 220-21
Neisser, Ulric., ed. (1998). *The Rising Curve*. Washington, DC: American Psychological Association.
Parente, Stephen L. and Edward C. Prescott. (2004). "A unified theory of the evolution of international income levels," Staff Report 333, Federal Reserve Bank of Minneapolis.
Parente, Stephen L. and Edward C. Prescott. (2002). *Barriers to Riches*, reprint edition. Cambridge, MA: MIT Press.
Prescott, Edward C. (1998). "Needed: A Theory of Total Factor Productivity." *International Economic Review*, *39*, 3, 525-51.
Sailer, Steven. (2004). "IQ and the Wealth of Nations, Lynn and Vanhanen: data table of national mean IQ studies." http://www.isteve.com/IQ_Table.htm

Xavier Sala-i-Martin, Gernot Doppelhofer, and Ronald I. Miller (2004), “Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach,” *American Economic Review*, *94*, 4, 813-835.

Sternberg, R. J. & Grigorenko, E. L. (2001) *Enviromental effects on cognitive abilities.* Mahwah, New Jersey: Lawrence Erlbaum Associates, Publishers.

Volken, T. (2003). “IQ and the Wealth of Nations. A Critique of Richard Lynn and Tatu Vanhanen's Recent Book,” *European Sociological Review, 19,* 411-412.

Warner, John T. and Saul Pleeter. “The Personal Discount Rate: Evidence from Military Downsizing Programs.” *American Economic Review*, *91*, 1, 33-53.

Weede, Erich, (2004). “Does Human Capital Strongly Affect Economic Growth Rates? Yes, but only If Assessed Properly.” *Comparative Sociology*, *3*, 2, 115-134.

Weede, Erich and Sebastian Kampf.. (2002). “The Impact of Intelligence and Institutional Improvements on Economic Growth,” *Kyklos, 55*,361-380.

Winship, C. and Korenman, S. (1997). Does Staying in School Make You Smarter? The Effect of Education on IQ in *The Bell Curve,* in *Intelligence, Genes, and Success: Scientists Respond to the Bell Curve.* New York, NY: Springer-Verlag.

Zax, Jeffrey S. and Daniel I. Rees. (2002). “IQ, Academic Performance, Environment, and Earnings,” *Review of Economics and Statistics, 84*, 4, 600-616.